Airbnb Price Prediction

Link to Colab Notebook: https://colab.research.google.com/drive/19Fgll-O7t-tENLw4_q5tn7KWz3DviDTf?usp=sharing

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Introduction

Problem Statement

The sharing economy has transformed travel, with Airbnb leading the way in accommodations. Pricing is pivotal: hosts aim for profitability while attracting guests, and guests seek value. This project focuses on developing a machine learning model to predict the log-transformed prices of Airbnb listings using structured data, helping hosts and Airbnb make informed, data-driven pricing decisions.

Motivation

The insights from this project can have significant practical implications for Airbnb's ecosystem.

- **For Hosts**: Help hosts set competitive and profitable rates, improving occupancy and revenue while reducing pricing uncertainties.
- **For Guests**: Enhance pricing transparency, enabling informed booking decisions and fostering trust in the platform.
- **For Airbnb**: Optimize pricing to boost bookings, improve listing competitiveness, and enhance user satisfaction across the ecosystem.
- **Broader Impact**: Demonstrate the power of machine learning to solve real-world business challenges and drive data-driven decision-making.

Executive Summary

This report explores the factors influencing Airbnb listing prices by analyzing extensive data on property attributes, host characteristics, and customer feedback. It leverages advanced data cleaning techniques and machine learning models to draw actionable insights.

Objectives

1. **Identify Key Price Determinants:** Evaluate which property attributes (e.g., location, size, amenities) and host features significantly impact listing prices.
2. **Model Robust Price Predictions:** Build predictive models to estimate prices with high accuracy and evaluate their performance using industry-standard metrics.
3. **Segment and Analyze Listings:** Uncover trends and patterns across different property types, neighborhoods, and pricing tiers to provide a strategic perspective.

Findings

1. **Best Model:** Gradient Boosting emerged as the most accurate predictor, with an RMSE of 0.34 and R-square of 73%, outperforming baseline models.
2. **Alternative Models:** Simpler models like Linear Regression, Ridge Regression, and SVR underperformed compared to Gradient Boosting, which proved to be the most effective in capturing complex data relationships.
3. **Feature Importance:** Top predictors include room type, number of bathrooms, location, number of bedrooms, and review scores.

Recommendations

1. **Optimize Listing Descriptions:** Hosts should emphasize high-impact features like location and private room types attract higher-paying customers.
2. **Focus on Key Segments:** Target marketing efforts on properties in premium locations to maximize revenue potential.
3. **Continuous Data Monitoring:** Regularly update and monitor listing data to refine models and adapt to market trends effectively.

Dataset

Data Source

We are utilizing a dataset from Kaggle that focuses on Airbnb listings, containing diverse features such as property details, host information, reviews, and pricing. The primary objective of this project is to predict the price of Airbnb listings based on these attributes.

Since Airbnb does not release official data on its marketplace listings, an independent organization, Inside Airbnb, scrapes and compiles publicly available information from the Airbnb website. For this project, we are using a dataset scraped in July 2016, which includes listings from six major U.S. cities: New York, Washington DC, San Francisco, Los Angeles, Chicago, and Boston.

Link to Inside Airbnb: https://insideairbnb.com/get-the-data/

Link to Kaggle: https://www.kaggle.com/datasets/stevezhenghp/airbnb-price-prediction

Dataset Description

This dataset contains 74,111 entries of Airbnb listings, with a total of 29 features. It includes detailed information about each listing, such as property details, host attributes, reviews, and location data. Below is an overview of the key features: Total Entries: 74,111 Total Features: 29 Memory Usage: ~15.9 MB

Data Dictionary

Feature	Type	Description
`id`	Numeric	Unique identifier for each Airbnb listing
`property_type`	Categorical	Type of property (e.g., Apartment, House, Condo)
`room_type`	Categorical	Type of room offered (e.g., Entire home/apt, Private room)
`amenities`	Text	List of amenities provided (e.g., TV, Kitchen)
`accommodates`	Numeric	Number of people the rental can accommodate
`bathrooms`	Numeric	Number of bathrooms (including full and half baths)
`bed_type`	Categorical	Type of bed provided (e.g., Real Bed, Futon)
`cancellation_policy`	Categorical	Host's cancellation policy (e.g., Flexible, Moderate, Strict)
`cleaning_fee`	Boolean	Indicates if a cleaning fee is charged to the customer or not(`True` / `False`)
`city`	Categorical	City where the listing is located (e.g., Boston, NYC, LA)
`description`	Text	Textual description of the property
`first_review`	Date	Date of the first guest review
`host_has_profile_pic`	Boolean	Indicates if the host has a profile picture (`True` / `False`)
`host_identity_verified`	Boolean	Indicates if the host's identity is verified (`True` / `False`)
`host_response_rate`	Numeric	Host's response rate to inquiries (percentage)
`host_since`	Date	Date when the host registered on Airbnb
`instant_bookable`	Boolean	Indicates if the property is available for instant booking (`True` / `False`)
`last_review`	Date	Date of the most recent review
`latitude`	Numeric	Geographic latitude of the listing
`longitude`	Numeric	Geographic longitude of the listing
`name`	Text	Name/title of the Airbnb listing

Feature	Type	Description
`neighbourhood`	Categorical	Informal neighborhood name (e.g., Downtown, Brooklyn Heights)
`number_of_reviews`	Numeric	Total number of reviews received
`review_scores_rating`	Numeric	Average review rating (0–100)
`thumbnail_url`	Text (URL)	URL of the property's primary photo
`zipcode`	Numeric	Zipcode of the listing's location
`bedrooms`	Numeric	Number of bedrooms in the property
`beds`	Numeric	Number of beds available in the property

Target Variable: log_price

The target variable, which represents the price of the Airbnb listing. This is the outcome variable we aim to predict based on the features.

Since log_price is a continuous numeric value, this problem is categorized as a regression problem. The goal of the model is to learn the relationship between the features and the target variable to accurately predict the log-transformed price of the listings.

```
!pip install scikit-optimize
```

```
Collecting scikit-optimize
  Downloading scikit_optimize-0.10.2-py2.py3-none-any.whl.metadata (9.7 kB)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-pa
Collecting pyaml>=16.9 (from scikit-optimize)
  Downloading pyaml-24.9.0-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: numpy>=1.20.3 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: scikit-learn>=1.0.0 in /usr/local/lib/python3.10/
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10
Downloading scikit_optimize-0.10.2-py2.py3-none-any.whl (107 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 107.8/107.8 kB 3.9 MB/s eta 0:00:00
Downloading pyaml-24.9.0-py3-none-any.whl (24 kB)
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-24.9.0 scikit-optimize-0.10.2
```

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import textwrap
```

```
# Load the dataset
file_name = 'https://drive.google.com/uc?export=download&id=1p9AIIGSHNY_PYHvytykJ8wP
data = pd.read_csv(file_name)

# Display basic information
data.head()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 29 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   id                      74111 non-null  int64  
 1   log_price               74111 non-null  float64
 2   property_type           74111 non-null  object 
 3   room_type               74111 non-null  object 
 4   amenities               74111 non-null  object 
 5   accommodates            74111 non-null  int64  
 6   bedrooms                74020 non-null  float64
 7   beds                    73980 non-null  float64
 8   bathrooms               73911 non-null  float64
 9   bed_type                74111 non-null  object 
 10  cancellation_policy     74111 non-null  object 
 11  cleaning_fee            74111 non-null  bool   
 12  city                    74111 non-null  object 
 13  description             74111 non-null  object 
 14  first_review            58247 non-null  object 
 15  host_has_profile_pic    73923 non-null  object 
 16  host_identity_verified  73923 non-null  object 
 17  host_response_rate      55812 non-null  object 
 18  host_since              73923 non-null  object 
 19  instant_bookable        74111 non-null  object 
 20  last_review             58284 non-null  object 
 21  latitude                74111 non-null  float64
 22  longitude               74111 non-null  float64
 23  name                    74111 non-null  object 
 24  neighbourhood           67239 non-null  object 
 25  number_of_reviews       74111 non-null  int64  
 26  review_scores_rating    57389 non-null  float64
 27  thumbnail_url           65895 non-null  object 
 28  zipcode                 73145 non-null  object 
dtypes: bool(1), float64(7), int64(3), object(18)
memory usage: 15.9+ MB
```

- Missing values are minimal for key features like bedrooms, beds, and bathrooms (less than 1%)
- Features such as host_response_rate, first_review, and review_scores_rating have significant missing values (20-25%), which may require imputation or exclusion based on the analysis
- All numeric features are stored as int64 or float64, making them ready for statistical analysis or modeling

Data Cleaning

Dropping unnecessary columns like id, description, and thumbnail_url as they do not provide meaningful or predictive information for the target variable.

```
columns_to_drop = ['id', 'description','thumbnail_url']
data = data.drop(columns=columns_to_drop)
```

Identifying which columns have missing values.

```
# Handle missing values
missing_values = data.isnull().sum()
print(f"Missing Values:\n{missing_values}")
```

```
Missing Values:
log_price                     0
property_type                 0
room_type                     0
amenities                     0
accommodates                  0
bedrooms                     91
beds                        131
bathrooms                   200
bed_type                      0
cancellation_policy           0
cleaning_fee                  0
city                          0
first_review              15864
host_has_profile_pic        188
host_identity_verified      188
host_response_rate        18299
host_since                  188
instant_bookable              0
last_review               15827
latitude                      0
longitude                     0
name                          0
neighbourhood              6872
number_of_reviews             0
review_scores_rating      16722
zipcode                     966
dtype: int64
```

Checking 'property_type' and 'room_type' columns that have missing 'bedrooms'

```
# Filter rows where 'bedrooms' is missing
missing_bedrooms = data[data['bedrooms'].isnull()]
```

```
# Dropping dupliactes from 'property_type' and 'room_type' columns
result = missing_bedrooms[['property_type', 'room_type','bedrooms']].drop_duplicates
print(result)
```

```
      property_type        room_type  bedrooms
200       Apartment  Entire home/apt       NaN
10513          Loft  Entire home/apt       NaN
11584         Other     Private room       NaN
11766     Apartment     Private room       NaN
24831         House  Entire home/apt       NaN
25806         House     Private room       NaN
33017         Villa     Private room       NaN
35976      Bungalow  Entire home/apt       NaN
39287   Condominium     Private room       NaN
```

Replacing null values in 'bedrooms' by median value as per the 'property_type'

```
# Replace null values in 'bedrooms' by the median of the same 'property_type'
data['bedrooms'] = data.groupby('property_type')['bedrooms'].transform(
    lambda x: x.fillna(x.median())
)
```

Replacing null values in 'beds' by assigning median value as per the 'bedrooms'

```
# Replace null values in 'beds' by the median of the same 'bedrooms'
data['beds'] = data.groupby('bedrooms')['beds'].transform(
    lambda x: x.fillna(x.median())
)
```

Replacing null values in 'bathrooms' by median value as per the 'bedrooms' and 'apartment_type'

```
# Replace null values in 'bathrooms' by the median after grouping by 'apartment_type
data['bathrooms'] = data.groupby(['property_type', 'bedrooms'])['bathrooms'].transfo
    lambda x: x.fillna(x.median())
)
```

Assuming that each property has atleast 1 bathroom, assigning the 'bathrooms' value as 1 where value is missing

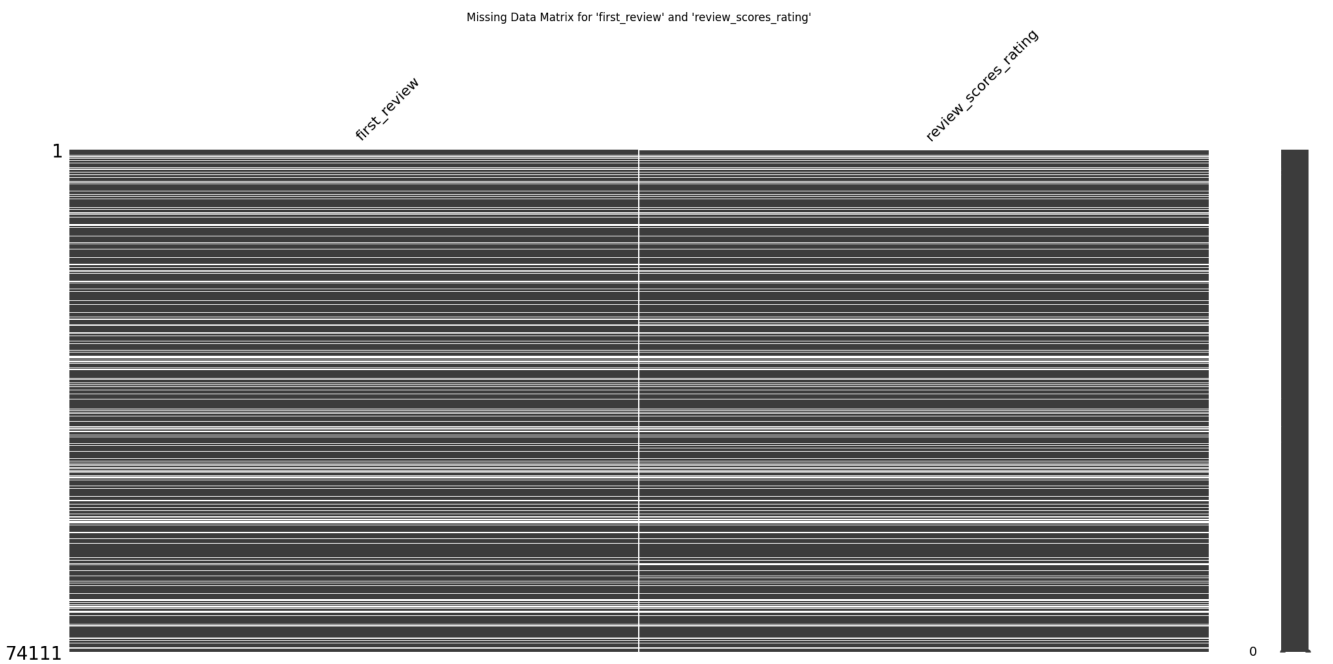
```
data.loc[data['bathrooms'].isnull(), 'bathrooms'] = 1
```

Understanding the relationship between missing values in 'first_review' and 'review_scores_rating' columns

```
missing_relationship = data[['first_review', 'review_scores_rating']].isnull().sum()
print("Missing values in 'first_review' and 'review_scores_rating':\n", missing_rela
```

```
Missing values in 'first_review' and 'review_scores_rating':
 first_review            15864
review_scores_rating    16722
dtype: int64
```

```
# Subset the dataset to include only the relevant columns
subset = data[['first_review', 'review_scores_rating']]

# Generate a matrix plot
msno.matrix(subset)
plt.title("Missing Data Matrix for 'first_review' and 'review_scores_rating'")
plt.show()
```

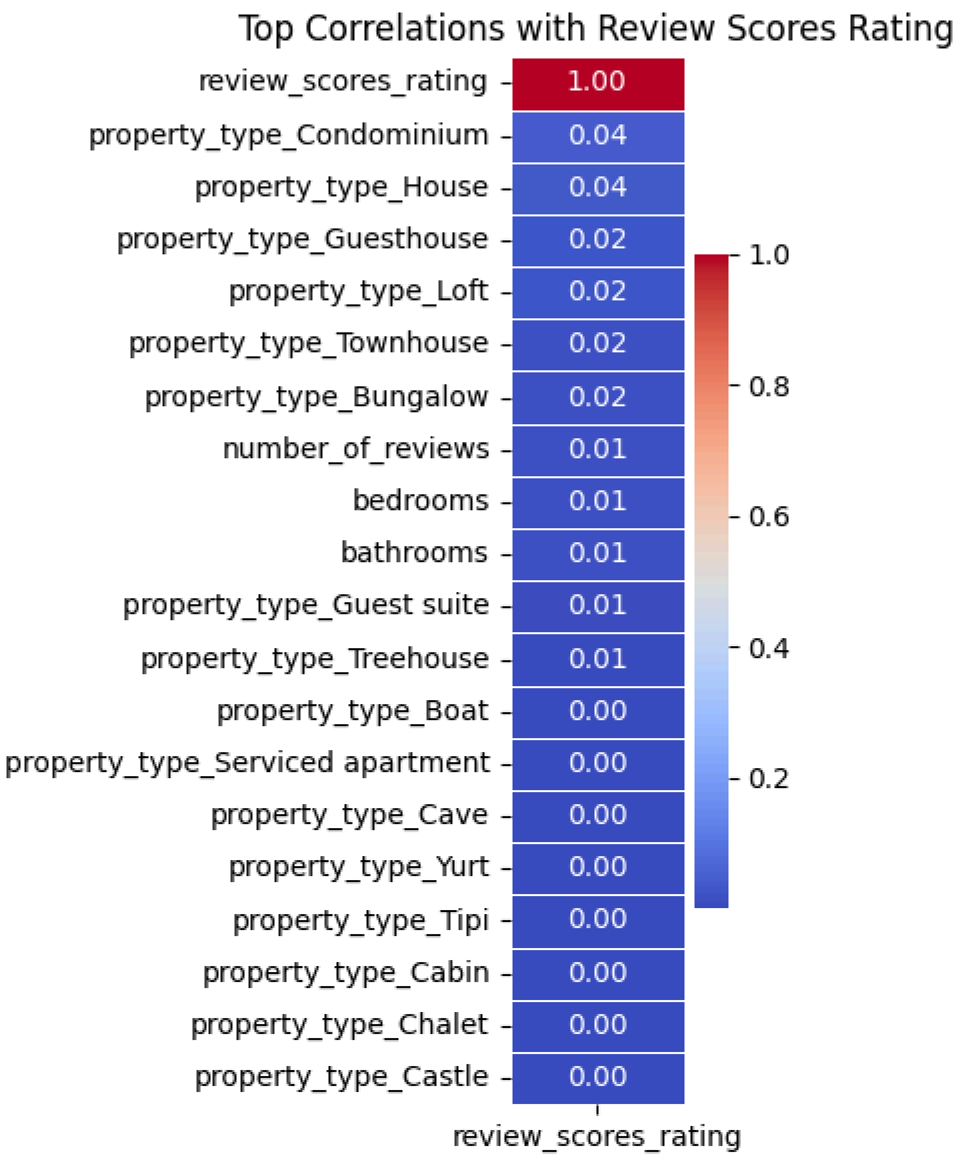


It was found that wherever 'first_review' has missing values, 'review_scores_rating' also has missing values. Hence, dropping null values in 'first_review' as these null values will affect our model.

```
data = data.dropna(subset=['first_review'])
```

Checking if 'review_scores_rating' has a correlation with any other column that can help us handle the null values in 'review_scores_rating' column.

```
# Select a smaller set of columns likely to influence 'review_scores_rating'
selected_columns = ['number_of_reviews', 'bedrooms', 'bathrooms', 'property_type', '

# Create a smaller DataFrame with only these columns and the target column
data_subset = data[selected_columns + ['review_scores_rating']]

# One-hot encode the categorical columns
categorical_columns = data_subset.select_dtypes(include=['object', 'category']).colu
data_encoded = pd.get_dummies(data_subset, columns=categorical_columns, drop_first=T

# Compute the correlation matrix
correlation_matrix = data_encoded.corr()

# Sort and plot top correlations with 'review_scores_rating'
corr_review_scores = correlation_matrix[['review_scores_rating']].dropna()
corr_review_scores = corr_review_scores.sort_values(by='review_scores_rating', ascen

plt.figure(figsize=(4, 6))
sns.heatmap(
    corr_review_scores,
    annot=True,
    cmap='coolwarm',
    fmt='.2f',
    linewidths=0.5,
    cbar=True
)
plt.title("Top Correlations with Review Scores Rating")
plt.xticks()
plt.tight_layout()
plt.show()
```



It is observed that no other column has a strong correlation with the 'review_scores_rating' column. Therefore, we will impute the missing values in 'review_scores_rating' using the median.

```
# Replace null values in 'review_scores_rating' with its median
data['review_scores_rating'] = data['review_scores_rating'].fillna(data['review_scor
```

Replacing null values in 'host_since' with the corresponding values from 'first_review'.

```
# Replace null values in 'host_since' with the corresponding values from 'first_revi
data['host_since'] = data['host_since'].fillna(data['first_review'])
```

Replacing missing 'host_has_profile_pic' with the mode of the column.

```
# Replace missing 'host_has_profile_pic' with the mode
mode_value = data['host_has_profile_pic'].mode()[0]
data['host_has_profile_pic'] = data['host_has_profile_pic'].fillna(mode_value)
```

Replacing missing values in 'host_identity_verified' according to the 'host_has_profile_pic'. If the host has profile pic then it is likely that their identity is verified.

```
# Replace missing 'host_identity_verified' based on 'host_has_profile_pic'
def impute_identity_verified(row):
    if pd.isnull(row['host_identity_verified']):
        if row['host_has_profile_pic'] == 't':
            return 't'  # Likely to be verified if they have a profile picture
        else:
            return 'f'  # Likely not verified if they don't have a profile picture`
    return row['host_identity_verified']  # Keep existing value

data['host_identity_verified'] = data.apply(impute_identity_verified, axis=1)
```

Handling null values in 'host_response_rate' by assigning median value according to the 'host_identity_verified'.

```
# Check if 'host_response_rate' contains strings or percentages
if data['host_response_rate'].dtype == 'object':
    # Remove '%' sign and convert to numeric
    data['host_response_rate'] = data['host_response_rate'].str.rstrip('%').astype(f

# Group by 'host_identity_verified' and fill missing 'host_response_rate' with the g
data['host_response_rate'] = data.groupby('host_identity_verified')['host_response_r
    lambda x: x.fillna(x.median())
)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 58247 entries, 0 to 74110
Data columns (total 26 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   log_price               58247 non-null  float64
 1   property_type           58247 non-null  object
 2   room_type               58247 non-null  object
 3   amenities               58247 non-null  object
 4   accommodates            58247 non-null  int64
 5   bedrooms                58247 non-null  float64
 6   beds                    58247 non-null  float64
 7   bathrooms               58247 non-null  float64
 8   bed_type                58247 non-null  object
 9   cancellation_policy     58247 non-null  object
```

```
 10  cleaning_fee            58247 non-null  bool
 11  city                    58247 non-null  object
 12  first_review            58247 non-null  object
 13  host_has_profile_pic    58247 non-null  object
 14  host_identity_verified  58247 non-null  object
 15  host_response_rate      58247 non-null  float64
 16  host_since              58247 non-null  object
 17  instant_bookable        58247 non-null  object
 18  last_review             58247 non-null  object
 19  latitude                58247 non-null  float64
 20  longitude               58247 non-null  float64
 21  name                    58247 non-null  object
 22  neighbourhood           53143 non-null  object
 23  number_of_reviews       58247 non-null  int64
 24  review_scores_rating    58247 non-null  float64
 25  zipcode                 57553 non-null  object
dtypes: bool(1), float64(8), int64(2), object(15)
memory usage: 11.6+ MB
```

Keeping null values in 'neighbourhood' and 'zipcode' columns for EDA. These columns will be dropped later to fit the model.

```
data.head()
```

	log_price	property_type	room_type	amenities	accommodates	bedroom
0	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3	1
1	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7	3
2	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5	1
4	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2	0
5	4.442651	Apartment	Private room	{TV,"Wireless Internet",Heating,"Smoke detecto...	2	1

5 rows × 26 columns

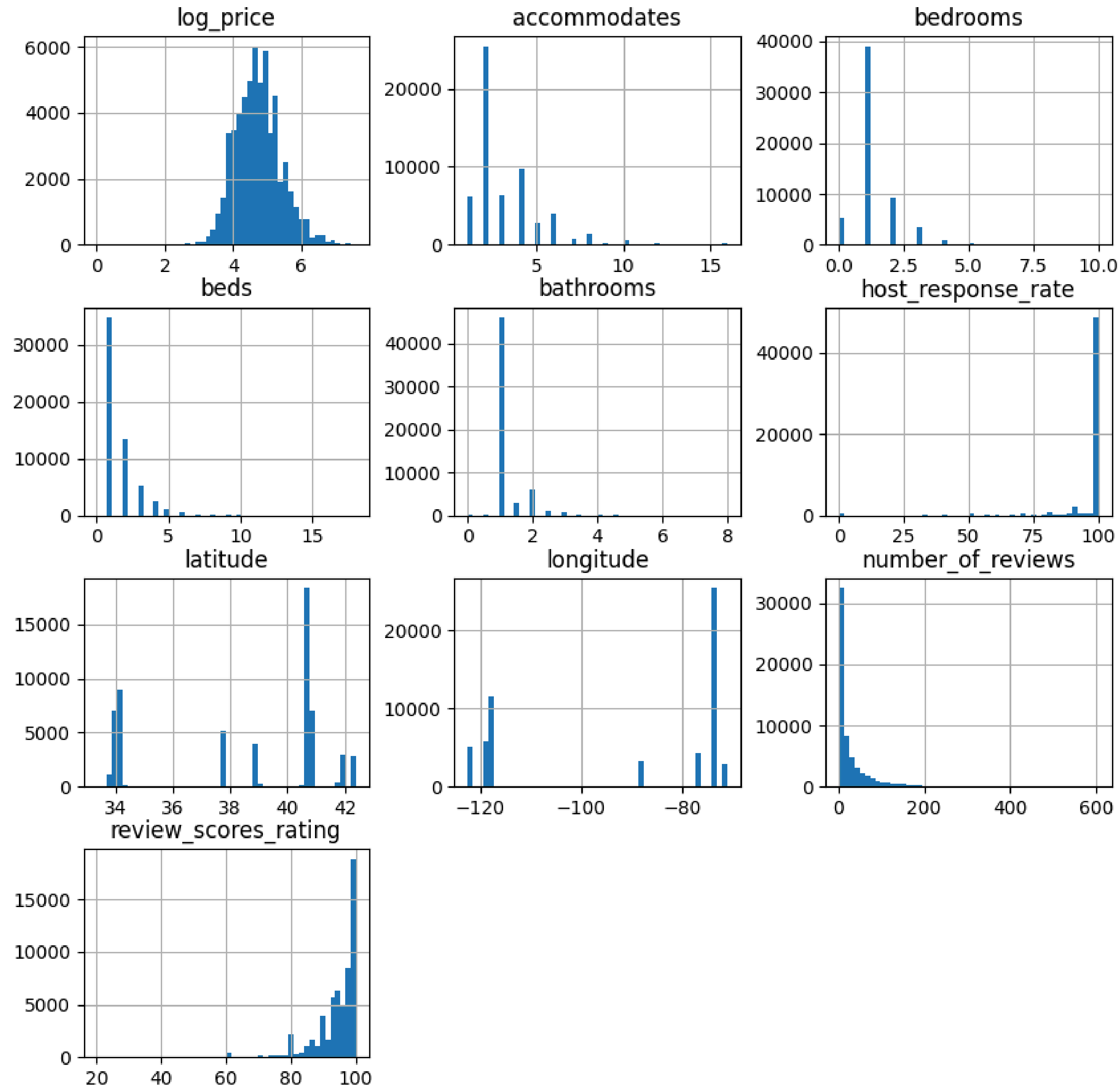
```
data.describe().round(2)
```

	log_price	accommodates	bedrooms	beds	bathrooms	host_response_rate
count	58247.00	58247.00	58247.00	58247.00	58247.00	58247.00
mean	4.75	3.21	1.26	1.74	1.23	96.21
std	0.67	2.14	0.84	1.27	0.56	12.51
min	0.00	1.00	0.00	0.00	0.00	0.00
25%	4.30	2.00	1.00	1.00	1.00	100.00
50%	4.70	2.00	1.00	1.00	1.00	100.00
75%	5.16	4.00	1.00	2.00	1.00	100.00

Exploratory Data Analysis

Histogram Matrix

```
data.hist(bins=50, figsize=(10, 10))
plt.show()
```



Based on the above histograms:

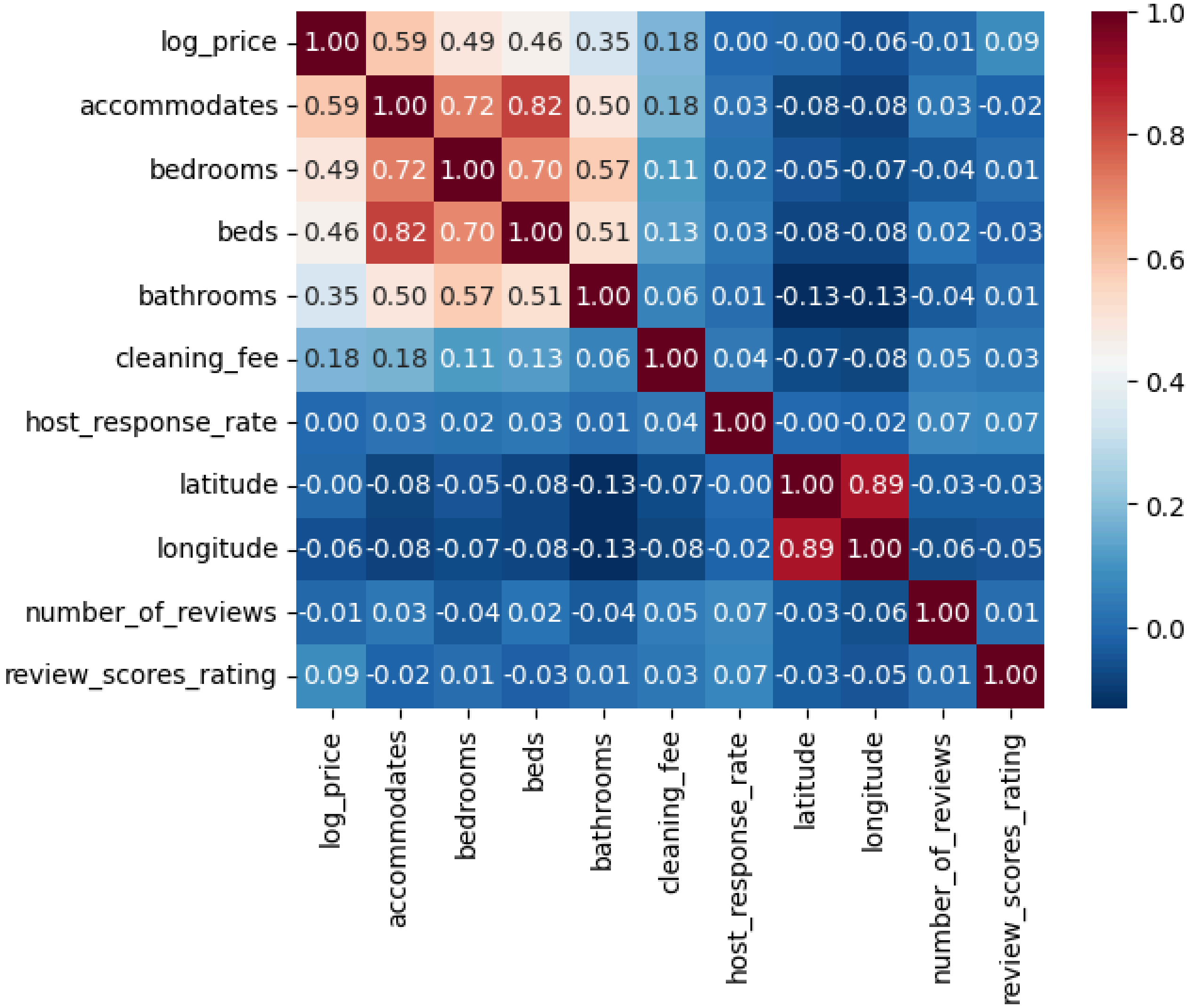
1. **log_price Distribution:** The log_price column shows a roughly normal distribution, indicating a relatively even spread of property prices (in log scale) with most values clustering around the

center.

2. **beds, bedrooms, and bathrooms:** These variables are heavily skewed to the right, with the majority of listings having a small number of beds, bedrooms, and bathrooms. This is expected for properties catering to smaller groups.
3. **number_of_reviews:** The distribution is highly right-skewed, with most properties having very few reviews, but a few outliers have a large number of reviews.
4. **Geographical Variables (latitude and longitude):** These show distinct clusters, likely corresponding to major cities or neighborhoods covered in the dataset.
5. **review_scores_rating:** The distribution is concentrated towards higher ratings, suggesting that most properties are well-reviewed.
6. **accommodates:** The chart shows that most properties accommodate a small number of guests, with a steep drop-off for larger capacities.

Heatmap

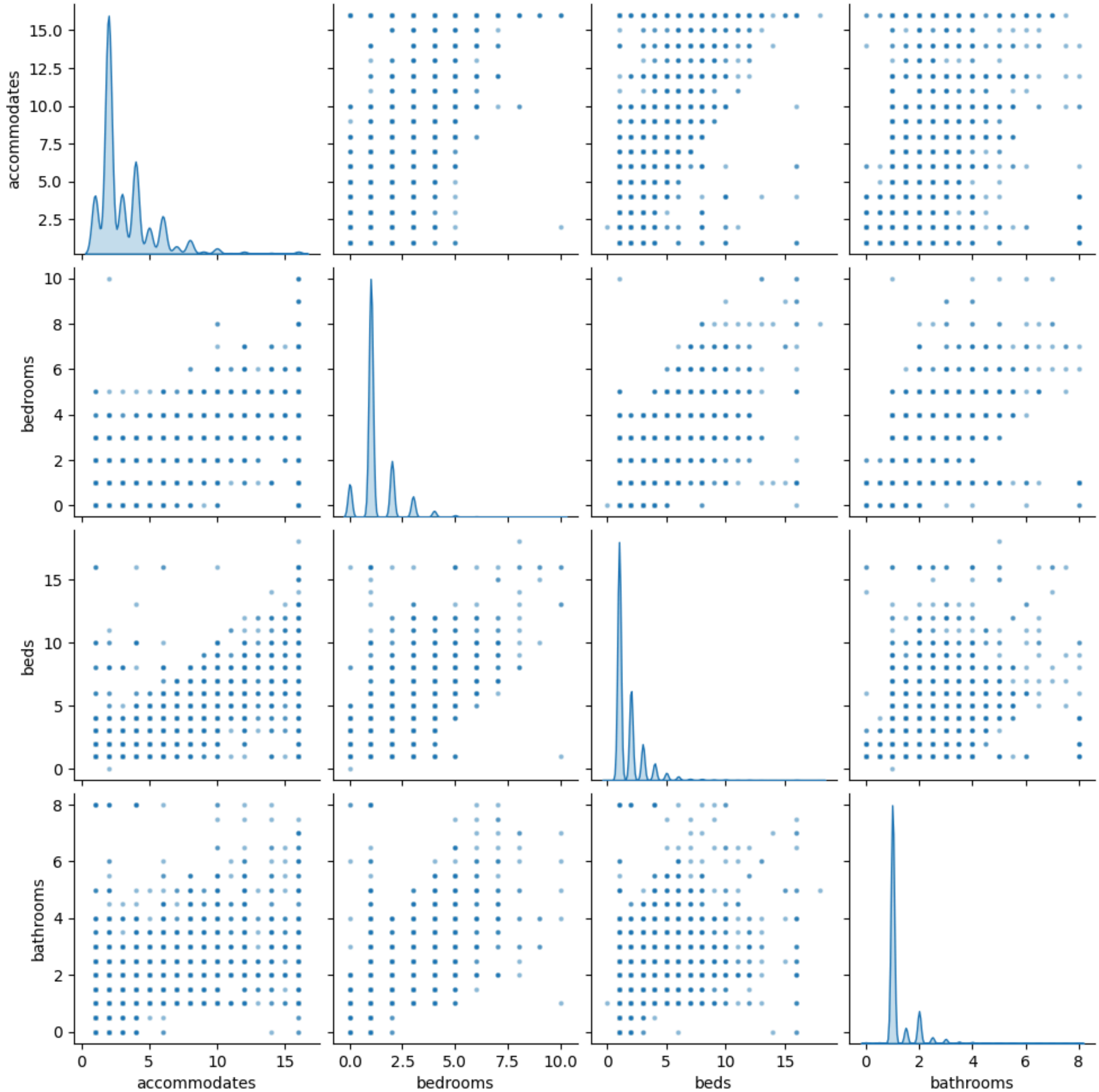
```
corr_matrix = data.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='RdBu_r');
```



Pairplots / scatter-matrices

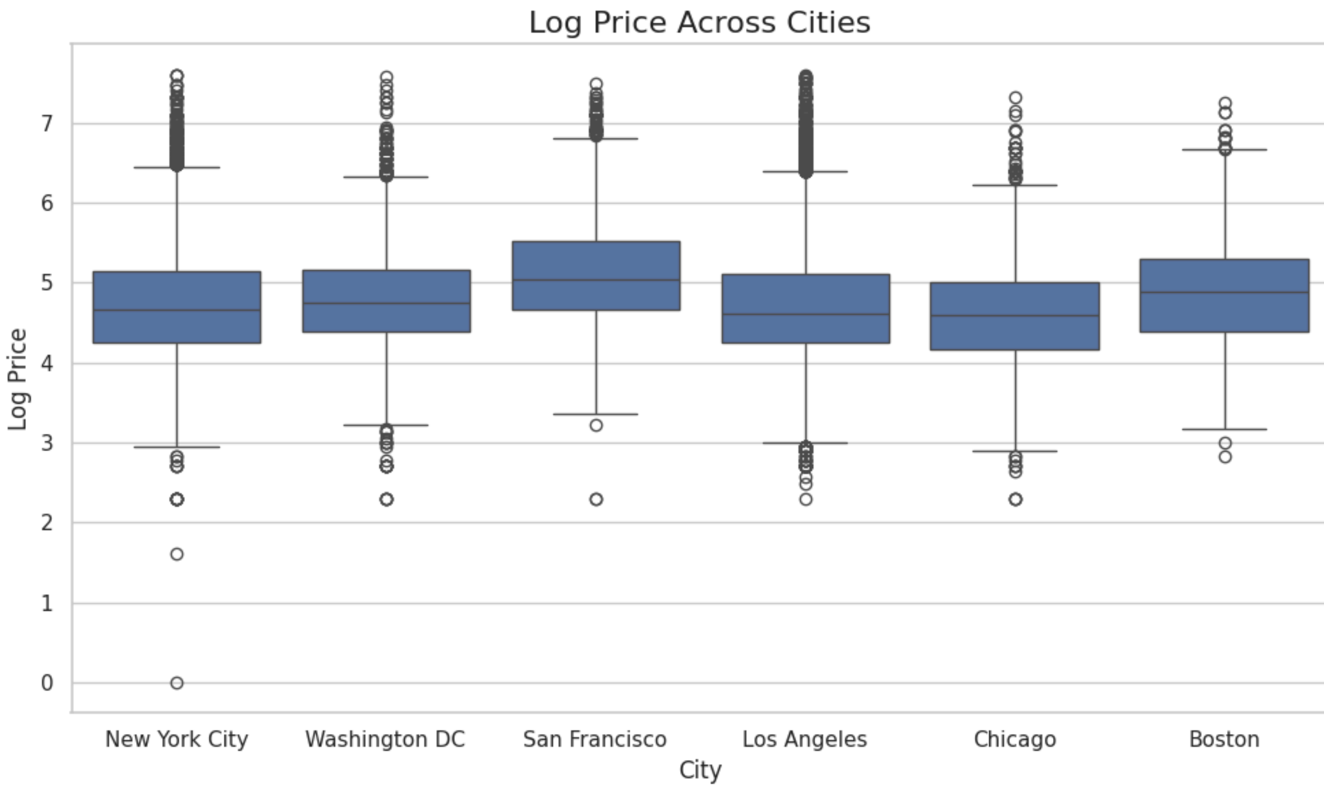
```
attributes = ["accommodates", "bedrooms", "beds", "bathrooms"]
sns.pairplot(data[attributes], diag_kind="kde", plot_kws={'s': 10, 'alpha': 0.5})
```

<seaborn.axisgrid.PairGrid at 0x7a01a9647280>



Log price across cities

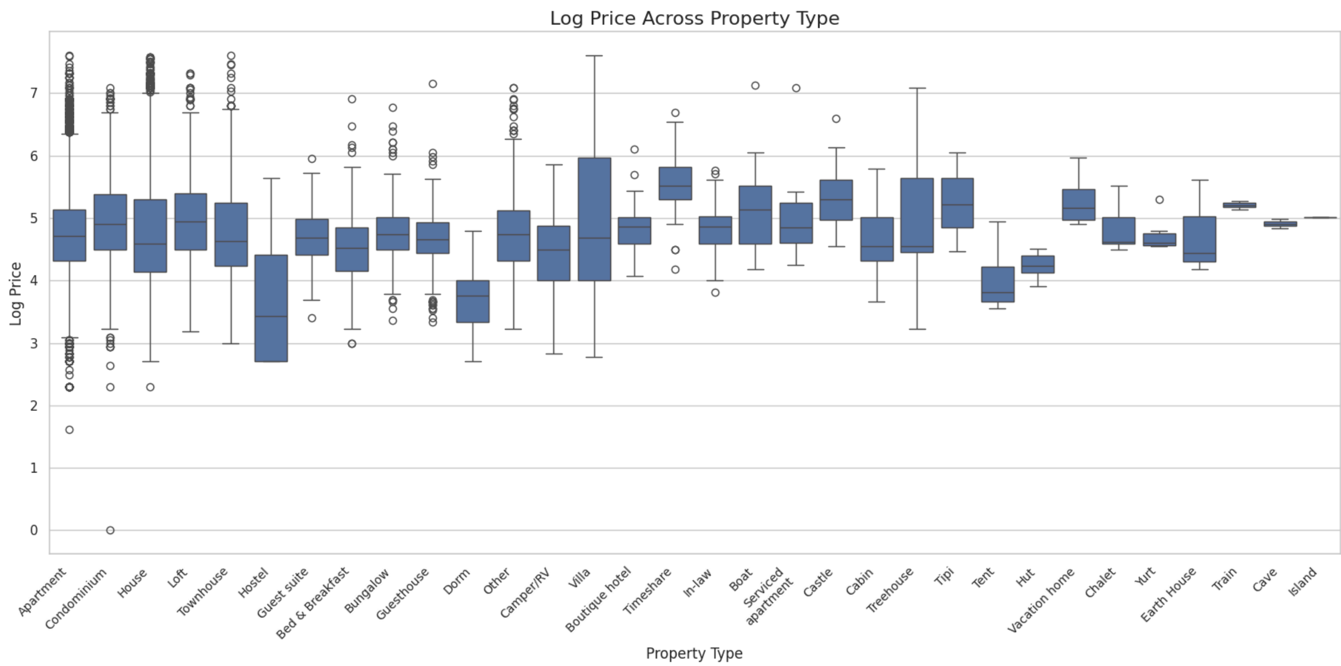
```
city_full_names = {
    'NYC': 'New York City',
    'LA': 'Los Angeles',
    'SF': 'San Francisco',
    'DC': 'Washington DC',
    'Chicago': 'Chicago',
    'Boston': 'Boston'
}

# Map abbreviations in 'city' column to full names
data['city_full_names'] = data['city'].map(city_full_names)

sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))
sns.boxplot(data=data, x='city_full_names', y='log_price')
plt.title('Log Price Across Cities', fontsize=16)
plt.xlabel('City', fontsize=12)
plt.ylabel('Log Price', fontsize=12)

plt.tight_layout()
plt.show()
```



- **City-Specific Pricing Trends:** The median log prices vary across cities, indicating that the city itself is a strong predictor of property prices. San Francisco and New York City exhibit higher median prices compared to other cities
- **Price Variability:** San Francisco and New York City also show a wider range of prices, with significant variability and numerous outliers, reflecting a diverse market with high-end and low-end properties
- **Relatively Stable Markets:** Cities like Boston, Chicago, and Washington DC display narrower interquartile ranges, suggesting more consistent pricing patterns and potentially less market volatility

Log Price Across Property Type

```
sns.set(style="whitegrid")
plt.figure(figsize=(16, 8))
sns.boxplot(data=data, x='property_type', y='log_price')
xticks_labels = [textwrap.fill(label, 15) for label in data['property_type'].unique(
plt.xticks(ticks=range(len(xticks_labels)), labels=xticks_labels, rotation=45, ha='r

plt.title('Log Price Across Property Type', fontsize=16)
plt.xlabel('Property Type', fontsize=12)
plt.ylabel('Log Price', fontsize=12)

plt.tight_layout()
plt.show()
```

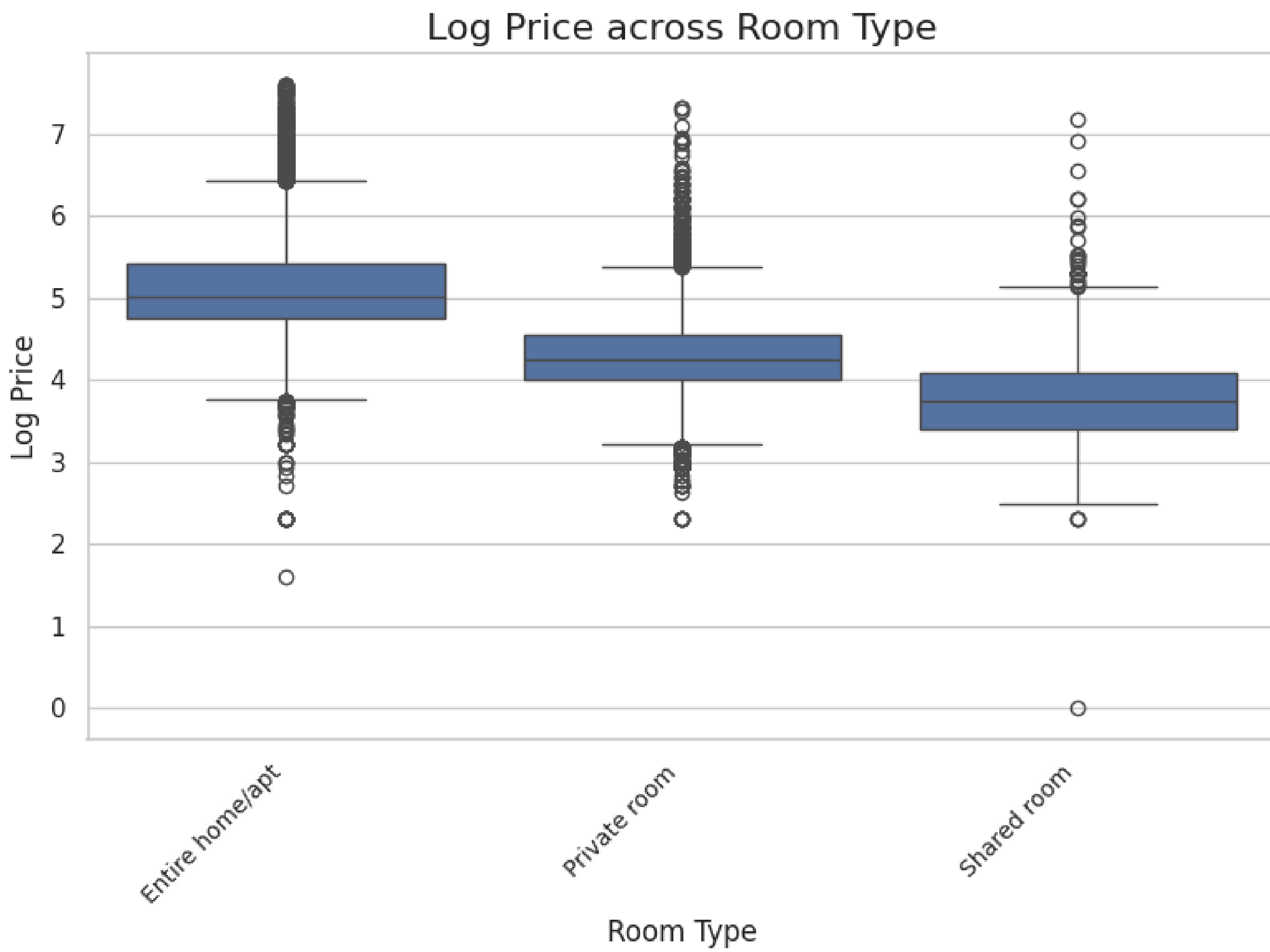


- **Property Type Variation:** The median log price varies significantly across property types, indicating that property type is a strong predictor of price in this dataset

- **Budget-Friendly Options:** Property types like "Hostel," "Guest Suite," and "Dorm" have lower median log prices and narrower interquartile ranges, pointing to consistent affordability and less variability in these categories
- **Common Residential Types:** Categories such as "Apartment," "House," and "Condominium" exhibit moderate median log prices with relatively tight distributions, indicating they are standard options with predictable pricing patterns, making them stable predictors.=
- **Diverse Price Ranges:** Some property types, such as "Guesthouse" and "Treehouse," span a wide range of prices, indicating that these categories capture a broad spectrum of customer preferences and pricing strategies

Log price across Room Types

```
sns.set(style="whitegrid")
plt.figure(figsize=(8, 6))
sns.boxplot(data=data, x='room_type', y='log_price')
xticks_labels = [textwrap.fill(label, 15) for label in data['room_type'].unique()]
plt.xticks(ticks=range(len(xticks_labels)), labels=xticks_labels, rotation=45, ha='r

plt.title('Log Price across Room Type', fontsize=16)
plt.xlabel('Room Type', fontsize=12)
plt.ylabel('Log Price', fontsize=12)

plt.tight_layout()
plt.show()
```



The chart shows significant differences in median log prices across room types, indicating that the room_type feature is a strong predictor for property pricing.

Properties with "Entire home/apt" have the highest median log price and variability, reflecting premium pricing, while "Private room" offers moderate pricing with less variability. "Shared room" is the most affordable option, with the lowest median price and limited flexibility.

Log Price across number of People Accommodated

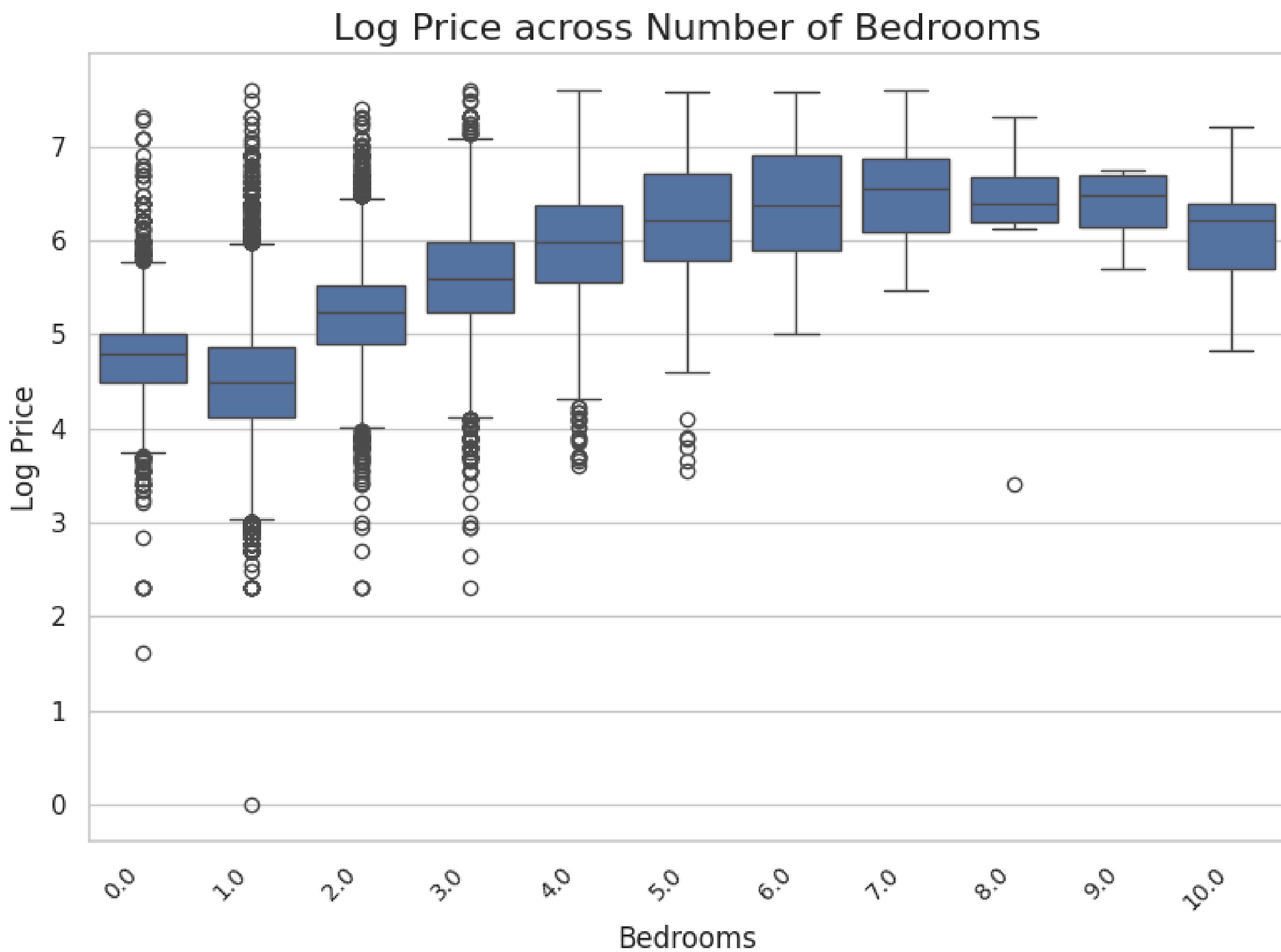
```
# Ensure the x-axis values are sorted numerically
accommodates_order = sorted(data['accommodates'].unique())

plt.figure(figsize=(8, 6))
sns.boxplot(data=data, x='accommodates', y='log_price', order=accommodates_order)
```

```
# Convert numerical values to strings before using textwrap.fill()
xticks_labels = [textwrap.fill(str(label), 15) for label in accommodates_order]

plt.xticks(ticks=range(len(xticks_labels)), labels=xticks_labels, rotation=45, ha='r

plt.title('Log Price across Number of People Accommodated', fontsize=16)
plt.xlabel('Accommodates', fontsize=12)
plt.ylabel('Log Price', fontsize=12)

plt.tight_layout()
plt.show()
```

- As the number of people a property accommodates increases, the log price generally rises, indicating higher prices for larger properties.
- Smaller properties (1-3 people) have consistent pricing with less variability, while larger accommodations (8+ people) show greater price variability.

Log prices across Bedrooms

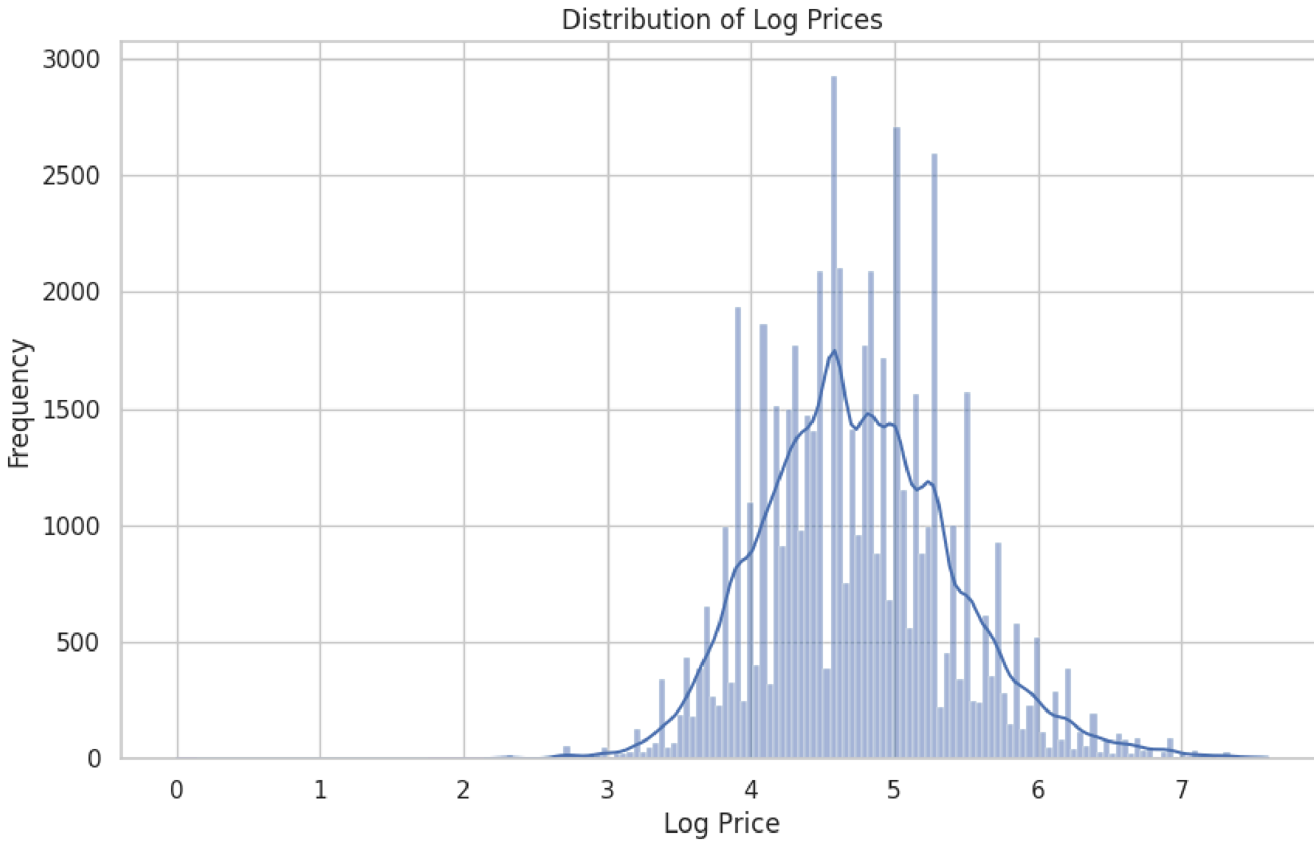
```
# Ensure the x-axis values are sorted numerically
bedrooms_order = sorted(data['bedrooms'].unique())

plt.figure(figsize=(8, 6))
sns.boxplot(data=data, x='bedrooms', y='log_price', order=bedrooms_order)

# Convert numerical values to strings before using textwrap.fill()
xticks_labels = [textwrap.fill(str(label), 15) for label in bedrooms_order]

plt.xticks(ticks=range(len(xticks_labels)), labels=xticks_labels, rotation=45, ha='r

plt.title('Log Price across Number of Bedrooms', fontsize=16)
plt.xlabel('Bedrooms', fontsize=12)
plt.ylabel('Log Price', fontsize=12)

plt.tight_layout()
plt.show()
```



- The chart shows that log price increases with the number of bedrooms, indicating that properties with more bedrooms generally command higher prices.
- Properties with 1-3 bedrooms have narrower price ranges, suggesting consistent pricing, whereas those with 4 or more bedrooms show greater variability, reflecting diverse property types (e.g., luxury or budget).

Distribution of Log Prices

```
plt.figure(figsize=(10, 6))
sns.histplot(data['log_price'], kde=True)
plt.title('Distribution of Log Prices')
plt.xlabel('Log Price')
plt.ylabel('Frequency')
plt.show()
```



The distribution of log-transformed prices is approximately normal with a slight right skew, centered around 4.5 to 5.

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 58247 entries, 0 to 74110
Data columns (total 27 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   log_price               58247 non-null  float64
 1   property_type           58247 non-null  object 
 2   room_type               58247 non-null  object 
 3   amenities               58247 non-null  object 
 4   accommodates            58247 non-null  int64  
 5   bedrooms                58247 non-null  float64
 6   beds                    58247 non-null  float64
 7   bathrooms               58247 non-null  float64
 8   bed_type                58247 non-null  object 
 9   cancellation_policy     58247 non-null  object 
```

```
 10  cleaning_fee           58247 non-null  bool
 11  city                   58247 non-null  object
 12  first_review           58247 non-null  object
 13  host_has_profile_pic   58247 non-null  object
 14  host_identity_verified  58247 non-null  object
 15  host_response_rate     58247 non-null  float64
 16  host_since             58247 non-null  object
 17  instant_bookable       58247 non-null  object
 18  last_review            58247 non-null  object
 19  latitude               58247 non-null  float64
 20  longitude              58247 non-null  float64
 21  name                   58247 non-null  object
 22  neighbourhood          53143 non-null  object
 23  number_of_reviews      58247 non-null  int64
 24  review_scores_rating   58247 non-null  float64
 25  zipcode                57553 non-null  object
 26  city_full_names        58247 non-null  object
dtypes: bool(1), float64(8), int64(2), object(16)
memory usage: 12.1+ MB
```

Removing Redundant and Irrelevant Features for Cleaner Modeling

In this step, we are removing unnecessary columns from the dataset to simplify analysis and reduce computational overhead. The columns below were identified as redundant or less relevant for predictive modeling:

- "name", "first_review", "last_review", "host_since": These columns contain high cardinality or free-text data that are not directly relevant to the predictive task and could complicate computation.
- "neighbourhood", "zipcode": These features might be redundant if similar spatial information is already captured by other features, such as latitude and longitude.
- "amenities": A high-cardinality text column that is difficult to parse and less useful in its raw form for prediction.
- "host_has_profile_pic", "host_identity_verified", "response_rate_range": These features are less likely to contribute significantly to model performance and can be dropped to streamline the dataset.

By dropping these columns, we create a cleaner, more focused dataset that prioritizes features with higher relevance to the predictive task, thereby improving efficiency and model interpretability.

```
# List of columns to drop
columns_to_drop = [
    "name", "first_review", "last_review", "host_since",
    "neighbourhood","zipcode","amenities",
     "host_has_profile_pic", "host_identity_verified", "response_rate_range"
]
```

```
# Dropping the columns
cleaned_data = data.drop(columns=columns_to_drop)

# Display the remaining columns
print("Remaining columns after dropping:")
print(cleaned_data.columns)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-33-d3d7ba458639> in <cell line: 9>()
      7
      8 # Dropping the columns
----> 9 cleaned_data = data.drop(columns=columns_to_drop)
     10
     11 # Display the remaining columns
```

3 frames

```
/usr/local/lib/python3.10/dist-packages/pandas/core/indexes/base.py in
drop(self, labels, errors)
   7068         if mask.any():
   7069             if errors != "ignore":
-> 7070                 raise KeyError(f"{labels[mask].tolist()} not found in
axis")
   7071             indexer = indexer[~mask]
   7072         return self.delete(indexer)

KeyError: "['response rate range'] not found in axis"
```

```
cleaned_data.info()
```

Machine Learning

Test-Train Split

Defining Features and Target:

- The feature variables (X) are obtained by dropping the target column ("log_price") from the dataset.
- The target variable (y) is set as the "log_price" column, which represents the variable to be predicted.

Splitting the Data:

- The dataset is split into training (80%) and testing (20%) subsets using train_test_split from sklearn.model_selection.
- A random_state of 42 is specified to ensure reproducibility, making the split consistent across different runs.

Resulting Dataset Shapes:

- The shapes of the training and testing datasets are displayed to confirm that the data has been correctly partitioned.
- By performing this split, we ensure the model is trained on one subset and evaluated on another, enabling an accurate assessment of its performance and generalizability.

```
from sklearn.model_selection import train_test_split

# Define the target variable (log_price) and features
X = cleaned_data.drop(columns=["log_price"])  # Features
y = cleaned_data["log_price"]                 # Target

# Perform the train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42  # 20% for testing, reproducibility with ra
)

# Display the shapes of the resulting datasets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

Preprocessing Pipeline

```
#Attempt 1 (using one-hot encoder, did not work):

'''
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn import set_config

# Enable diagram visualization
set_config(display="diagram")

# Identify column types
numerical_cols = X_train.select_dtypes(include=["float64", "int64"]).columns.tolist(
categorical_cols = X_train.select_dtypes(include=["object"]).columns.tolist()
boolean_cols = X_train.select_dtypes(include=["bool"]).columns.tolist()

# Preprocessing for numerical features
numerical_preprocessor = Pipeline(steps=[
    ("scaler", StandardScaler())
```

```
])

# Preprocessing for categorical features
categorical_preprocessor = Pipeline(steps=[
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])

# Preprocessing for boolean features
class BooleanTransformer(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X.astype(int)

boolean_preprocessor = Pipeline(steps=[
    ("boolean_transformer", BooleanTransformer())
])

# Combine preprocessors into a column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ("num", numerical_preprocessor, numerical_cols),
        ("cat", categorical_preprocessor, categorical_cols),
        ("bool", boolean_preprocessor, boolean_cols)
    ]
)

# Full pipeline
pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor)
])

# Display the pipeline diagram
pipeline
'''
```

This code creates a preprocessing pipeline for handling numerical, categorical, and boolean features, using StandardScaler for numerical data, OneHotEncoder for categorical data, and a custom transformer for boolean data. While it is well-structured, it uses one-hot encoding, which increases the feature space significantly by creating binary columns for each category. This can slow down model training and complicate feature selection.

Instead, target encoding is used in the project as it numerically represents categorical features based on their relationship with the target variable. This reduces dimensionality, improves computational efficiency, and simplifies feature selection, making it better suited for this dataset.

```
# Attempt 2 (using Target encoding, worked):

!pip install category_encoders

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from category_encoders import TargetEncoder
from sklearn.base import BaseEstimator, TransformerMixin
import pandas as pd

# Step 1: Preprocess Boolean Columns in X_train and X_test
# Convert 't'/'f' to 1/0 in boolean columns
boolean_cols = [col for col in X_train.columns if X_train[col].nunique() == 2]

for col in boolean_cols:
    X_train[col] = X_train[col].replace({'t': 1, 'f': 0})
    X_test[col] = X_test[col].replace({'t': 1, 'f': 0})

# Step 2: Define Column Groups Based on X_train
numerical_cols = X_train.select_dtypes(include=["int64", "float64"]).columns.tolist(
categorical_cols = X_train.select_dtypes(include=["object"]).columns.tolist()

# Step 3: Define the Preprocessing Pipeline
# Custom Boolean Transformer for boolean columns
class BooleanTransformer(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X.astype(int)

# Preprocessing for numerical features
numerical_preprocessor = Pipeline(steps=[
    ("scaler", StandardScaler())
])

# Preprocessing for categorical features (Target Encoding with smoothing)
categorical_preprocessor = Pipeline(steps=[
    ("target_encoder", TargetEncoder(smoothing=0.3))
])

# Preprocessing for boolean features
boolean_preprocessor = Pipeline(steps=[
    ("boolean_transformer", BooleanTransformer())
])

# Combine preprocessors into a ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ("num", numerical_preprocessor, numerical_cols),
```

```
        ("cat", categorical_preprocessor, categorical_cols),
        ("bool", boolean_preprocessor, boolean_cols)
    ]
)

# Full preprocessing pipeline
pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor)
])

pipeline
```

Fitting Preprocessing Pipeline to the training & testing data

```
# Fit the pipeline to the training data (features and target)
pipeline.fit(X_train, y_train)

# Transform both training and testing data
X_train_processed = pipeline.transform(X_train)


# Verify the output shape
print("Processed training data shape:", X_train_processed.shape)
```

Model Evaluation and Comparison Using Cross-Validation

```
'''
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.svm import SVR
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
import numpy as np

# Ensure the preprocessing pipeline is applied to the data
X_train_preprocessed = pipeline.transform(X_train)

# Define models to evaluate
models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(alpha=1.0),  # Default alpha
    "Support Vector Regressor": SVR(kernel='linear', C=1.0, epsilon=0.1),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42)
}

# Compare models
```

```
model_scores = {}

for model_name, model in models.items():
    # Perform 5-fold cross-validation
    neg_mse_scores = cross_val_score(
        model, X_train_preprocessed, y_train, cv=5, scoring="neg_mean_squared_error"
    )
    rmse_scores = np.sqrt(-neg_mse_scores)  # Convert negative MSE to RMSE
    mean_rmse = rmse_scores.mean()  # Average RMSE

    # Store the results
    model_scores[model_name] = mean_rmse
    print(f"{model_name} Cross-Validation RMSE: {mean_rmse:.2f}")

# Find the best model based on RMSE
best_model_name = min(model_scores, key=model_scores.get)
print(f"\nBest Model: {best_model_name} with RMSE: {model_scores[best_model_name]:.2
'''
```

The initial code for model evaluation faced significant delays as it sequentially performed 5-fold cross-validation for each model without leveraging available computational resources effectively. To address this, parallel processing was introduced in the updated code using the joblib library with threading. This approach allowed multiple folds of cross-validation to run simultaneously across available processors, drastically reducing computation time while maintaining accuracy. By efficiently utilizing system resources, the second implementation ensured faster results without compromising on model evaluation quality.

This code evaluates multiple regression models using cross-validation to compare their performance based on Root Mean Squared Error (RMSE) and R^2 (coefficient of determination). The preprocessed training data ensures that all models—Linear Regression, Ridge Regression, Support Vector Regressor, and Gradient Boosting Regressor—operate on consistent, cleaned features.

Using 5-fold cross-validation, each model is trained on four data subsets and tested on the remaining one, rotating until all subsets are used. RMSE quantifies prediction accuracy (lower is better), while R^2 explains the variance captured by the model (closer to 1 is better). Parallel processing (parallel_backend) optimizes execution speed, especially for complex models like Gradient Boosting.

Finally, RMSE and R^2 scores are compared, and the best-performing model is selected based on the lowest RMSE. This approach ensures robust evaluation and helps identify the most accurate and explanatory model for the given dataset.

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression, Ridge
```

```
from sklearn.svm import SVR
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import make_scorer, r2_score
import numpy as np
from joblib import parallel_backend

# Pre-cache transformed data
X_train_preprocessed = pipeline.transform(X_train)

# Define models
models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(alpha=1.0),
    "Support Vector Regressor": SVR(kernel='linear', C=1.0, epsilon=0.1),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42)
}

# Compare models
model_scores = {}

for model_name, model in models.items():
    with parallel_backend('threading'):  # Use parallel processing
        # Cross-validation for RMSE
        neg_mse_scores = cross_val_score(
            model, X_train_preprocessed, y_train, cv=5, scoring="neg_mean_squared_er
        )
        rmse_scores = np.sqrt(-neg_mse_scores)
        mean_rmse = rmse_scores.mean()

        # Cross-validation for R²
        r2_scores = cross_val_score(
            model, X_train_preprocessed, y_train, cv=5, scoring=make_scorer(r2_score
        )
        mean_r2 = r2_scores.mean()

    # Store results
    model_scores[model_name] = {"RMSE": mean_rmse, "R2": mean_r2}
    print(f"{model_name} Cross-Validation RMSE: {mean_rmse:.2f}, R2: {mean_r2:.2f}")

# Best model
best_model_name = min(model_scores, key=lambda x: model_scores[x]["RMSE"])
print(f"\nBest Model: {best_model_name} with RMSE: {model_scores[best_model_name]['R
```

Analyzing Feature Importance for Gradient Boosting Model

This block of code focuses on analyzing feature importance to identify the most relevant features for the Gradient Boosting model. Initially, the Gradient Boosting Regressor is trained using the preprocessed training data, after which the feature_importances_ attribute of the model is used to extract the relative importance of each feature. These importance values represent the contribution of each feature to the model's predictive performance. The corresponding feature names are retrieved from the preprocessing pipeline, ensuring alignment with the extracted importance values.

The features are then sorted based on their importance, and only those with non-zero importance are considered relevant. This helps focus on the features that actively contribute to the model's predictions, eliminating noise from less significant variables. A bar plot is generated to visually display the importance of these relevant features, making it easier to interpret their relative impact on the model. This step provides valuable insights into the dataset and guides further feature selection or refinement for improved model performance.

```
import pandas as pd
import matplotlib.pyplot as plt

# Step 1: Train the Gradient Boosting model
best_model = GradientBoostingRegressor(random_state=42)
best_model.fit(X_train_preprocessed, y_train)

# Step 2: Extract feature importances
feature_importances = best_model.feature_importances_

# Step 3: Extract feature names from the pipeline
feature_names = []
for name, transformer, columns in pipeline.named_steps["preprocessor"].transformers_
    if name == "remainder" and transformer == "passthrough":
        feature_names.extend(columns)
    elif name == "bool":
        feature_names.extend(columns)
    elif hasattr(transformer, "get_feature_names_out"):
        feature_names.extend(transformer.get_feature_names_out(columns))
    else:
        feature_names.extend(columns)

# Ensure feature names match feature importances
if len(feature_names) != len(feature_importances):
    feature_names = feature_names[:len(feature_importances)]  # Truncate if necessar

# Step 4: Create a DataFrame for feature importances
importance_df = pd.DataFrame({
    "Feature": feature_names,
    "Importance": feature_importances
}).sort_values(by="Importance", ascending=False)

# Step 5: Filter relevant features (importance > 0)
relevant_features_df = importance_df[importance_df["Importance"] > 0]

# Display the relevant features
print("Relevant Features:")
```

```
print(relevant_features_df)

# Step 6: Plot relevant features and their importance
plt.figure(figsize=(12, 8))
plt.barh(relevant_features_df["Feature"], relevant_features_df["Importance"], color=
plt.xlabel("Feature Importance")
plt.ylabel("Feature")
plt.title("Relevant Features Based on Importance")
plt.gca().invert_yaxis()  # Invert y-axis for better readability
plt.tight_layout()
plt.show()
```

Fine-Tuning the Model

This code focuses on leveraging the most relevant features identified in the feature importance analysis to retrain the Gradient Boosting model and evaluate its performance. By selecting only the most impactful features, we aim to enhance the model's efficiency while maintaining or improving its predictive accuracy.

In this implementation, key features such as room_type, bathrooms, and longitude are identified and extracted from the preprocessed training data. The model is then retrained using only these selected features. After training, predictions on the training data are generated to calculate performance metrics like Root Mean Squared Error (RMSE) and R-squared (R^2). This approach not only streamlines the modeling process but also emphasizes the importance of selecting high-impact features for improved model performance and interpretability.

```
# Step 1: Define the selected features
selected_features = [
    "room_type",
    "bathrooms",
    "longitude",
    "accommodates",
    "bedrooms",
    "latitude",
    "city",
    "review_scores_rating"
]

# Step 2: Identify indices of selected features in the preprocessed data
selected_indices = [feature_names.index(feature) for feature in selected_features]

# Step 3: Filter the training and test data for selected features
X_train_selected = X_train_preprocessed[:, selected_indices]
```

```
print(f"Shape of training data after selecting features: {X_train_selected.shape}")

# Step 4: Retrain the Gradient Boosting model with the selected features
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Initialize and train the model
final_model = GradientBoostingRegressor(random_state=42)
final_model.fit(X_train_selected, y_train)

# Predict on the training data
y_train_pred = final_model.predict(X_train_selected)

# Step 5: Evaluate the model
rmse = mean_squared_error(y_train, y_train_pred, squared=False)
r2 = r2_score(y_train, y_train_pred)

print("\nModel Performance with Selected Features:")
print(f"RMSE: {rmse:.2f}")
print(f"R-squared: {r2:.2f}")
```

Optimizing Hyperparameters with Randomized Search

This code block performs hyperparameter tuning using RandomizedSearchCV to find the best combination of parameters for the Gradient Boosting Regressor. By exploring a predefined parameter distribution, the search process tests multiple combinations to minimize the Root Mean Squared Error (RMSE).

The parameter grid includes hyperparameters like the number of estimators, learning rate, maximum depth of trees, and subsampling rate. RandomizedSearchCV is configured to evaluate 20 random combinations across 3-fold cross-validation, balancing thoroughness with efficiency. After the search, the best hyperparameters and the corresponding RMSE are displayed. This process ensures that the model is optimized for better predictive performance while reducing the computational cost of an exhaustive search.

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import GradientBoostingRegressor
import numpy as np

# Define parameter distribution for Randomized Search (optimized for speed)
param_dist = {
    'n_estimators': [50, 100, 150],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 5],
```

```
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'subsample': [0.8, 1.0],
    'max_features': ['sqrt', None]
}

# Initialize RandomizedSearchCV with reduced iterations and cross-validation folds
random_search = RandomizedSearchCV(
    GradientBoostingRegressor(random_state=42),
    param_distributions=param_dist,
    n_iter=20,
    scoring="neg_mean_squared_error",
    cv=3,
    verbose=1,
    n_jobs=-1,  # Use all available processors
    random_state=42
)

# Perform search
random_search.fit(X_train_selected, y_train)

# Display results
best_params_random = random_search.best_params_
best_rmse_random = np.sqrt(-random_search.best_score_)

print("\n--- Optimized Randomized Search Results ---")
print(f"Best Parameters: {best_params_random}")
print(f"Best RMSE: {best_rmse_random:.2f}")
```

Hyperparameter tuning with Grid Search

This code block performs hyperparameter tuning using GridSearchCV to systematically evaluate all possible combinations of specified hyperparameters for the Gradient Boosting Regressor. The search space includes key parameters such as the number of estimators, learning rate, maximum tree depth, and subsampling rate.

To balance thoroughness and computational efficiency, the parameter grid is defined with a reduced range of values, resulting in 128 parameter combinations. Using 2-fold cross-validation, the total number of fits is reduced to 256, making the search more manageable while covering important configurations. The best-performing parameters are selected based on the lowest Root Mean Squared Error (RMSE), ensuring the model is optimally tuned for better predictive accuracy.

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingRegressor
```

```
import numpy as np

# Define smaller parameter grid for ~100-150 fits
param_grid_old = {
    'n_estimators': [100, 150],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 5],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'subsample': [0.8, 1.0],
    'max_features': ['sqrt', None]
}
#we increased the search space to further tune the model for better prediction

param_grid = {
    'n_estimators': [100, 150, 200, 300],
    'learning_rate': [0.01, 0.03, 0.05, 0.1],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.6, 0.8, 0.9, 1.0],
    'max_features': ['sqrt', 'log2', None]
}

cv_folds = 2  # Use 2-fold CV to reduce fits to ~128 x 2 = 256 total

# Initialize GridSearchCV
grid_search = GridSearchCV(
    GradientBoostingRegressor(random_state=42),
    param_grid=param_grid,
    scoring="neg_mean_squared_error",
    cv=cv_folds,
    verbose=1,
    n_jobs=-1
)

# Perform search
grid_search.fit(X_train_selected, y_train)

# Retrieve the best parameters and RMSE
best_params_grid = grid_search.best_params_
best_rmse_grid = np.sqrt(-grid_search.best_score_)

# Display results
print("\n--- Optimized Grid Search Results ---")
print(f"Best Parameters: {best_params_grid}")
print(f"Best RMSE: {best_rmse_grid:.2f}")
```

Hyperparameter Tuning with Bayesian Optimization

This code block uses Bayesian Optimization via BayesSearchCV from the scikit-optimize library to efficiently tune hyperparameters for the Gradient Boosting Regressor. Unlike Grid and Randomized Search, Bayesian Optimization uses a probabilistic model to explore the search space, focusing on promising configurations based on previous results.

The search space includes important hyperparameters like the number of estimators, learning rate, maximum depth of trees, and subsampling ratio. Using 30 iterations across 3-fold cross-validation, the search adaptively selects the next set of hyperparameters based on the lowest Root Mean Squared Error (RMSE). This targeted exploration helps minimize unnecessary computations while ensuring optimal performance. The best hyperparameters and the corresponding RMSE are displayed, demonstrating how Bayesian Optimization efficiently balances search coverage and model accuracy.

```
from skopt import BayesSearchCV
from skopt.space import Real, Integer, Categorical
from sklearn.ensemble import GradientBoostingRegressor
import numpy as np

# Define the search space
search_space = {
    'n_estimators': Integer(50, 150),
    'learning_rate': Real(0.01, 0.1, prior='log-uniform'),
    'max_depth': Integer(3, 5),
    'min_samples_split': Integer(2, 10),
    'min_samples_leaf': Integer(1, 5),
    'subsample': Real(0.8, 1.0),
    'max_features': Categorical(['sqrt', None])
}

# Initialize Bayesian Search
bayes_search = BayesSearchCV(
    GradientBoostingRegressor(random_state=42),
    search_spaces=search_space,
    n_iter=30,
    scoring="neg_mean_squared_error",
    cv=3,
    verbose=1,
    n_jobs=-1,
    random_state=42
)

# Perform the search
bayes_search.fit(X_train_selected, y_train)
```

```
# Retrieve the best parameters and RMSE
best_params_bayes = bayes_search.best_params_
best_rmse_bayes = np.sqrt(-bayes_search.best_score_)

# Display results
print("\n--- Optimized Bayesian Search Results ---")
print(f"Best Parameters: {best_params_bayes}")
print(f"Best RMSE: {best_rmse_bayes:.2f}")
```

Preprocessing test data with selected features

```
# Transform the test data using the trained pipeline
X_test_preprocessed = pipeline.transform(X_test)

# Extract feature names from the pipeline
feature_names = []
for name, transformer, columns in pipeline.named_steps["preprocessor"].transformers_
    if name == "remainder" and transformer == "passthrough":
        feature_names.extend(columns)
    elif name == "bool":
        feature_names.extend(columns)
    elif hasattr(transformer, "get_feature_names_out"):
        feature_names.extend(transformer.get_feature_names_out(columns))
    else:
        feature_names.extend(columns)

# Define selected features
selected_features = [
    "room_type",
    "bathrooms",
    "longitude",
    "accommodates",
    "bedrooms",
    "latitude",
    "city",
    "review_scores_rating"
]

# Identify indices of selected features in the preprocessed data
selected_indices = [feature_names.index(feature) for feature in selected_features if

# Filter the test data for selected features
X_test_selected = X_test_preprocessed[:, selected_indices]

# Verify the output shape
print(f"Shape of test data after selecting features: {X_test_selected.shape}")
```

Model Evaluation

```
from sklearn.metrics import mean_squared_error, r2_score
import plotly.graph_objects as go

# Use the best parameters from GridSearchCV
best_model = GradientBoostingRegressor(**best_params_grid, random_state=42)
best_model.fit(X_train_selected, y_train)

# Generate predictions on training and test sets
y_train_pred = best_model.predict(X_train_selected)
y_test_pred = best_model.predict(X_test_selected)

# Evaluate Regression Metrics
rmse_train = mean_squared_error(y_train, y_train_pred, squared=False)
rmse_test = mean_squared_error(y_test, y_test_pred, squared=False)

r2_train = r2_score(y_train, y_train_pred)
r2_test = r2_score(y_test, y_test_pred)

# Display Regression Metrics
print("\nModel Evaluation Metrics (Regression)")
print(f"Training RMSE: {rmse_train:.2f}, R²: {r2_train:.2f}")
print(f"Test RMSE: {rmse_test:.2f}, R²: {r2_test:.2f}")

# Create a bar chart for regression metrics
metrics_df = pd.DataFrame({
    "Metric": ["Training RMSE", "Test RMSE", "Training R²", "Test R²"],
    "Value": [rmse_train, rmse_test, r2_train, r2_test]
})

# Plot Regression Metrics using Plotly
fig_metrics = go.Figure(
    data=[
        go.Bar(
            x=metrics_df["Metric"],
            y=metrics_df["Value"],
            text=metrics_df["Value"].round(2),
            textposition="auto",
            marker=dict(color='skyblue')
        )
    ]
)
fig_metrics.update_layout(
    title="Regression Model Evaluation Metrics",
    xaxis_title="Metric",
    yaxis_title="Score",
    yaxis=dict(range=[0, 1.0]),
    template="plotly_white"
```